International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

ADVANCED AI FRAMEWORK FOR URBAN SAFETY THROUGH MANHOLE INSPECTION AND MAINTENANCE

***S Roshan Manuel** [1], #**Mr. J.Jayapandian** [2]*

[1]Master of Computer Applications, Krishnasamy College of Engineering &Technology, Cuddalore,India
[2]MCA.,M.Phil.,(Ph.D).,Associate Professor, Master of Computer Applications, Krishnasamy College of Engineering &Technology, Cuddalore,India.

ABSTRACT :

Manholes are critical to urban infrastructure, providing access to systems like sewers and electrical conduits, but damaged, open, or missing covers pose serious safety risks. Traditional manual inspections are time-consuming, error-prone, and inefficient, especially in large cities. This project proposes an automated deep learning-based inspection system that leverages Convolutional Neural Networks (CNN) for classification and YOLOv8 for real-time detection and localization. Trained on a diverse dataset, the system classifies manholes into categories such as Closed, Open, Broken, Overflow, and No Manhole. By incorporating UAV and CCTV footage, it ensures wide-area coverage and accurate detection even in complex environments. The automated system reduces human error, enables faster responses, and improves safety while optimizing maintenance efforts, offering a scalable and reliable solution for modern urban infrastructure management. Additionally, integrating Region Proposal Networks (RPN) improves localization accuracy, while GLCM enhances texture-based feature extraction. The web-based platform allows easy access to inspection results, making it user-friendly for municipal staff. The project supports predictive maintenance by identifying early signs of wear. Overall, it contributes to smarter, safer, and more sustainable city management.

Keywords—Manhole, Machine learning, Deep learning, Automation, Manhole Automation, Manhole detection.

INTRODUCTION

Manholes are critical elements of urban utility infrastructure, offering access to essential underground systems such as sewage lines, electrical conduits, and stormwater drains. They are commonly found in public roads, sidewalks, and industrial zones. However, when these manhole covers become open, broken, displaced, or entirely missing, they pose a serious threat to public safety. Pedestrians, cyclists, and vehicles are especially vulnerable to injuries and accidents caused by such defects. Maintaining the integrity of manhole covers is, therefore, a priority for municipal safety and infrastructure reliability.

Traditional inspection of manholes depends heavily on manual observation by trained inspectors, who assess the condition of manhole covers and document their findings in checklists or reports. Although this method has been used for years, it is inherently limited by human error, subjectivity, and the high labor demands of large-scale urban monitoring. The manual process is often reactive, addressing problems only after incidents occur. Additionally, the growing size and complexity of urban environments make frequent inspections increasingly difficult and inefficient.

To overcome these limitations, the proposed system introduces a deep learning-based automated inspection solution that can classify and detect manhole defects with high accuracy. The system aims to make the inspection process proactive, reliable, and scalable by leveraging advanced image processing and AI techniques. It utilizes Convolutional Neural Networks (CNNs) to classify manhole images into categories such as ‘Closed,’ ‘Open,’ ‘Broken,’ ‘Overflow,’ and ‘No Manhole.’ These models are trained on a diverse dataset to learn intricate patterns and variations in visual features.
To enhance detection performance, the system also integrates You Only Look Once version 8 (YOLOv8), a real-time object detection model known for its speed and precision. YOLOv8 enables the system to not only classify images but also localize the exact position of the manhole in a scene. Complementing this is the Region Proposal Network (RPN), which focuses on identifying potential object regions within an image, thereby improving detection efficiency. Additionally, the Grey-Level Co-occurrence Matrix (GLCM) is used to extract texture features, helping to distinguish between subtle surface-level variations in manhole appearances.

Data for training the model is collected from multiple sources including Google Street View, UAV (drone) imagery, and CCTV footage from urban areas. The inclusion of aerial and ground-level perspectives ensures that the model is robust against diverse lighting, angles, and environmental conditions. UAVs allow for efficient monitoring of large and inaccessible areas, while CCTV provides continuous surveillance in high-traffic zones. This integration enhances both the coverage and reliability of the system.

The output of the system is displayed through a user-friendly web interface that presents real-time classification and localization results. This interface helps maintenance personnel to identify and prioritize manholes needing urgent attention, view their locations on a digital map, and plan repairs accordingly. The platform not only improves operational efficiency but also provides a centralized and accessible system for infrastructure management teams.

Overall, this project provides a scalable and intelligent solution to the challenges of modern urban infrastructure maintenance. By automating the detection and classification process, it reduces the burden of manual inspections, minimizes the risk of oversight, and significantly enhances public safety. The system empowers cities to adopt a proactive maintenance strategy, reduces emergency repair costs, and ensures that manhole-related hazards are addressed before they lead to accidents

LITERATURE SURVEY

1. Deep Learning Based Object Detection And Classification

Convolutional Neural Networks (CNNs) have emerged as a cornerstone of modern computer vision, owing to their ability to automatically learn and extract hierarchical features from raw image data. Since their introduction by Krizhevsky et al. in 2012 through the development of AlexNet, CNNs have revolutionized image classification by outperforming traditional machine learning models that required manual feature extraction. These networks utilize layers of convolutions, activations, and pooling operations to detect spatial patterns such as edges, textures, and complex shapes. Their deep layered architecture allows CNNs to learn both low-level and high-level features, making them particularly effective for recognizing objects, analyzing scenes, and detecting subtle anomalies within images. Over the years, CNNs have been widely adopted across industries—from facial recognition and autonomous driving to medical imaging and industrial inspection—demonstrating their versatility and robustness. In the context of infrastructure monitoring, CNNs have been successfully employed to detect various types of road surface damage, cracks in bridges, potholes, and other structural faults. Their application eliminates the need for manual inspection and provides a scalable solution for large-scale urban environments. This capability is especially valuable in scenarios where consistency, accuracy, and speed are essential, such as the real-time monitoring of safety-critical infrastructure. For manhole inspection, CNNs offer a powerful tool to classify the condition of manhole covers by learning discriminative features associated with categories like 'closed', 'open', 'broken', 'overflow', and 'no manhole'. Unlike traditional image processing techniques that rely heavily on thresholding or edge detection, CNNs are capable of adapting to varying image conditions, including changes in lighting, shadows, occlusions, or background clutter. This makes them a reliable solution for outdoor applications that involve dynamic and often unpredictable environments.

2. Region-Based Techniques For Localization

Region Proposal Networks (RPNs) play a crucial role in object detection by efficiently generating candidate regions where objects are likely to be found. Introduced by Ren et al. in 2015 as a core component of the Faster R-CNN architecture, RPNs revolutionized the field of object detection by replacing traditional, computationally expensive region proposal methods like Selective Search with a neural network that can predict object bounds and objectness scores simultaneously. This advancement significantly improved both the speed and accuracy of object detection pipelines.

In the context of infrastructure monitoring—particularly for tasks like manhole detection—RPNs are especially useful because they can precisely localize objects in cluttered, noisy, and visually complex environments typical of urban scenes. Urban imagery often contains a multitude of overlapping features such as road markings, vehicles, pedestrians, and shadows, making the task of detecting specific infrastructure elements more difficult. RPNs address this by narrowing down the areas of interest, allowing the system to focus only on regions that are likely to contain manholes, which improves overall system performance.

Additionally, RPNs are fully integrated with deep learning-based object detection frameworks, enabling end-to-end training and real-time deployment. This integration allows for better optimization of features extracted from convolutional layers and improves the model's ability to learn spatial hierarchies within the image. When used in conjunction with downstream classifiers such as CNNs, RPNs act as a powerful tool for isolating manhole structures before passing them on for further classification into categories like 'Open', 'Closed', or 'Broken'.

3. Real Time Detection With YOLO

The **You Only Look Once (YOLO)** object detection framework has revolutionized real-time object detection with its unique single-stage architecture, offering a highly efficient alternative to traditional two-stage detectors like R-CNN and Faster R-CNN. Unlike its predecessors, YOLO processes the entire image in one pass, significantly reducing detection time while maintaining high accuracy. Among its various iterations, **YOLOv8**, the latest in the series, brings significant
enhancements in both performance and versatility. Built upon the success of earlier versions, YOLOv8 incorporates improvements in model architecture, training strategies, and post-processing techniques, resulting in faster inference speeds, improved object localization, and greater resilience to diverse input conditions.

Studies by **Redmon et al.**, who initially introduced YOLO, have consistently emphasized the model's ability to strike a balance between speed and precision—an essential factor for real-world applications such as autonomous driving, surveillance, and urban infrastructure monitoring. YOLOv8 takes this further by adopting advanced attention mechanisms, better feature extraction backbones, and optimized anchor-free detection methods, all of which contribute to higher detection accuracy across a wide range of object sizes and shapes. These improvements make YOLOv8 particularly wellsuited for use in dynamic and uncontrolled environments, such as city streets, where manhole covers may vary in appearance due to wear, lighting, angle, or occlusion.

4. Texture-Based Image Analysis for Urban Infrastructure Condition Monitoring

Texture feature extraction methods, such as the **Gray-Level Co-occurrence Matrix (GLCM)**, play a vital role in image-based analysis by capturing the spatial relationship and distribution patterns of pixel intensities in an image. GLCM works by measuring how often pairs of pixel values with specific spatial relationships occur in a given image, allowing for the extraction of important texture features like contrast, correlation, energy, and homogeneity. These features provide valuable information about the surface characteristics of objects, making GLCM a widely adopted technique in various domains such as **surface inspection, crack detection, material analysis, and pavement condition monitoring**. In the context of manhole inspection, GLCM is particularly effective in identifying subtle surface anomalies that might not be easily detected through color or shape alone. By analyzing the texture patterns on manhole covers—such as wear, corrosion, or cracks—GLCM contributes additional insight that strengthens the overall image classification process. When combined with **Convolutional Neural Networks (CNNs)**, which excel at extracting high-level semantic features, GLCM enhances the model's ability to differentiate between conditions like *intact*, *damaged*, or *worn-out* surfaces. This hybrid approach results in improved accuracy, especially in challenging scenarios involving poor lighting, shadows, or dirt-covered surfaces. Therefore, integrating GLCM into the system complements deep learning techniques and adds robustness to the detection and classification pipeline.

5. Advanced Integration of UAV Technology for Enhanced Infrastructure Data Acquisition

One of the most significant challenges in traditional infrastructure monitoring lies in the **limited accessibility and visibility** of critical components, especially in densely populated urban environments or hazardous locations. Ground-based inspections are often constrained by obstructions, traffic, and safety risks, while stationary surveillance systems may lack the flexibility needed to monitor hard-to-reach or elevated areas. To overcome these limitations, the **integration of Unmanned Aerial Vehicles (UAVs)**—commonly known as drones—and existing **Closed-Circuit Television (CCTV)** networks has emerged as a highly effective and complementary strategy for infrastructure inspection and monitoring.

One of the most significant challenges in traditional infrastructure monitoring lies in the **limited accessibility and visibility** of critical components, especially in densely populated urban environments or hazardous locations. Ground-based inspections are often constrained by obstructions, traffic, and safety risks, while stationary surveillance systems may lack the flexibility needed to monitor hard-to-reach or elevated areas. To overcome these limitations, the **integration of Unmanned Aerial Vehicles (UAVs)**—commonly known as drones—and existing **Closed-Circuit Television (CCTV)** networks has emerged as a highly effective and complementary strategy for infrastructure inspection and monitoring.

PROPOSED SYSTEM

The proposed Manhole Predictor system is a web-based deep learning application designed to automate manhole maintenance and improve public safety. It classifies manholes into four categories—closed, open, broken, or no manhole—by processing images from sources like Google Street View and local authorities.

The workflow includes pre-processing (grayscale conversion, resizing, and noise filtering), followed by segmentation using Region Proposal Network (RPN) to detect regions of interest. Grey-Level Co-occurrence Matrix (GLCM) is then used for extracting texture features, and a Convolutional Neural Network (CNN) is trained to perform classification. The final prediction and localization are handled by YOLOv8, offering accurate detection and visualization on a web interface for easy access by maintenance personnel.

RPN plays a key role in object detection by generating anchor boxes that propose potential object regions in an image, which are refined further through bounding box regression and classification. GLCM complements this by analyzing texture through the frequency of pixel intensity pairs, providing statistical features like contrast, energy, and correlation—useful for identifying surface anomalies on manholes. Together, RPN and GLCM enhance detection accuracy, especially under difficult conditions like dirt, cracks, or low-light scenarios.

CNN and YOLOv8 form the backbone of the system's classification and detection capabilities. CNNs learn hierarchical visual features using convolutional and pooling layers, ultimately predicting manhole states with high accuracy. YOLOv8, the latest version of the YOLO family, improves upon its predecessors with deeper architectures, anchor boxes, and faster real-time detection. It processes entire images in a single forward pass, delivering both class probabilities and bounding box coordinates. The integration of these models creates a powerful and scalable solution for smart urban infrastructure monitoring.

YOLOv8 also incorporates advanced techniques like mosaic augmentation and label smoothing to boost detection robustness. Its lightweight architecture enables deployment on edge devices, such as drones or CCTV systems, for real-time operation in the field. By combining CNN's strength in classification and YOLOv8's precision in localization, the system ensures both accuracy and speed. This makes it ideal for large-scale deployment in cities for continuous, automated manhole monitoring.

Architecture Design Flow

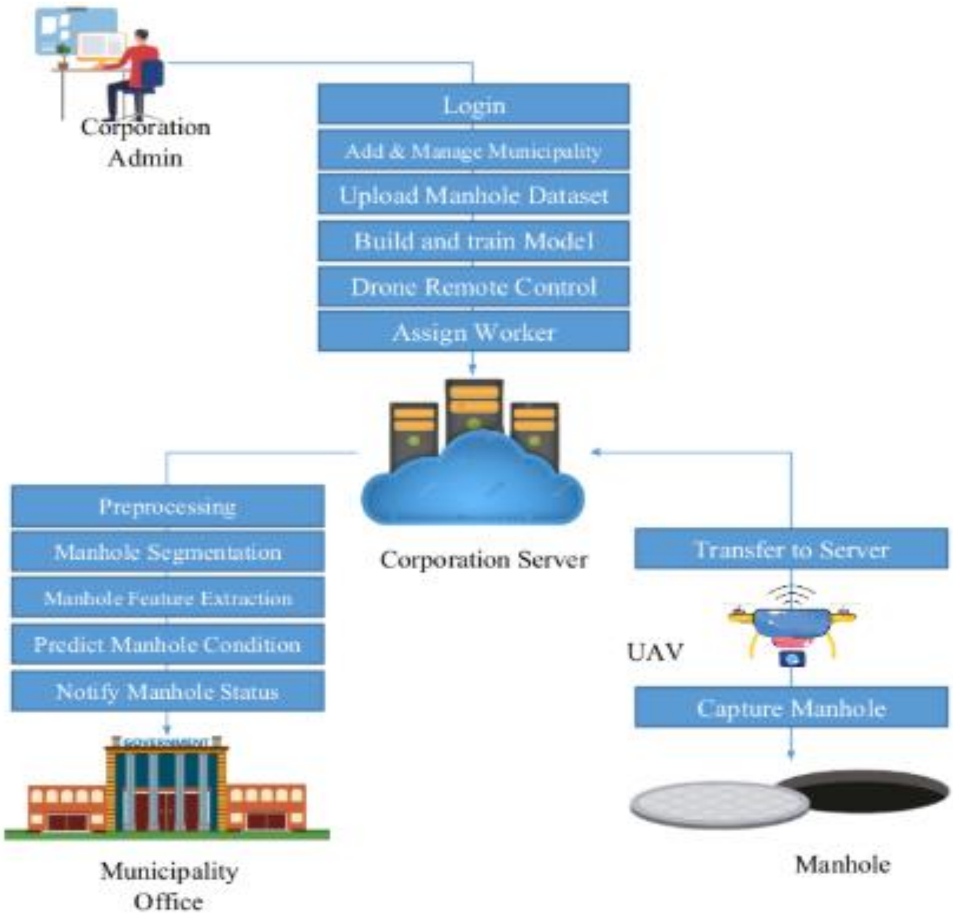


Figure 1: System Architecture of the proposed system

The system architecture of the automated manhole inspection project involves multiple components working together to ensure efficient maintenance. The process begins with the *Corporation Admin*, who logs into the system to manage municipalities, upload manhole datasets, train models, control UAVs, and assign workers. UAVs are deployed to *capture images of manholes*, even in hard-to-reach areas, and then *transfer the captured data* to the *corporation server*.

Once the images reach the server, the system performs *preprocessing*, including noise reduction and grayscale conversion. This is followed by *segmentation* to isolate manhole regions and *feature extraction* using techniques like GLCM. The system then uses trained CNN and YOLOv8 models to *predict the manhole condition*—whether it's open, closed, broken, or missing. After prediction, the *status is sent to the Municipality Office*, which can then take immediate action.

This automated workflow ensures *real-time monitoring*, reduces manual labor, and improves urban safety

3.1 IMPLEMENTATION

Our project constituted of the below modules,

- Manhole Predictor Web App
- End User Interface
- Manhole Classifier: Build and Train
- Manhole Predictor
- Notification

1. Manhole Predictor Web App

The *Manhole Predictor* web application is a deep learning-based system developed using Python, Flask, and MySQL. The front-end, built with HTML, CSS, and JavaScript, offers a simple interface for uploading manhole images, viewing prediction results, and interacting with the system

The back-end, powered by Flask, handles key operations like image processing, classification, and localization using CNN and YOLOv8. It also manages communication between the front-end and the database, enabling accurate and efficient processing of manhole data.

The MySQL database stores user data, images, and prediction results securely. User authentication and authorization are managed using Flask-Security, allowing only registered users to access the system. This integrated approach ensures reliability, security, and usability for urban infrastructure monitoring.

2.End User Interface

The Manhole Predictor Web App offers a clean, user-friendly interface tailored for web admins, citizens, and municipality officers. Web admins can log in securely to train models, manage users, and monitor system performance. Citizens can upload manhole images and instantly receive predictions such as open, closed, broken, or missing. Users also have access to their prediction history and can download results for future reference. Municipality officers can view defected manholes with image location and severity levels. This helps prioritize and schedule repairs efficiently.

Each user role has a dedicated interface with specific features, ensuring ease of use and functionality. The interfaces are intuitive, requiring no technical expertise. The system enhances urban infrastructure monitoring through public participation and administrative coordination.

3.Manhole Classifier: Build and Train

The *Manhole Classifier module* is the core component responsible for training and deploying machine learning models that classify manhole images based on their condition. It begins with *dataset collection*, where manhole images in different states (e.g., open, closed, broken, overflow, or no manhole) are gathered through web scraping and user uploads. These images are then imported and displayed using Python libraries like OpenCV and Matplotlib, allowing users to verify and filter the dataset visually. A *pre-processing phase* follows, involving grayscale conversion, resizing, denoising, and binarization to prepare images for model training.

After pre-processing, the system performs *segmentation* using a Region Proposal Network (RPN) and ROI pooling to extract specific regions of interest in the image. These regions are passed to the *feature extraction module*, which applies the Gray-Level Co-occurrence Matrix (GLCM) technique to generate texture features such as contrast, homogeneity, and correlation. These extracted features are essential for accurate classification and are stored for training purposes.

The final step is *classification and training*. A Convolutional Neural Network (CNN) is used to classify manhole images into their respective categories. The CNN architecture includes convolutional, pooling, and fully connected layers to learn and detect patterns from the image data. The *Build and Train module* handles network architecture definition, hyperparameter tuning, training, evaluation, and model deployment. Once trained, the model is integrated into the web application for real-time manhole condition prediction and monitoring. The training process uses labeled data to learn distinctive features associated with each manhole condition. Performance is validated using metrics like accuracy, precision, and recall to ensure reliability. The trained model is also optimized for efficiency to support fast predictions on user-uploaded images. This integration allows stakeholders to detect and respond to defects quickly, enhancing urban infrastructure maintenance.

4. Manhole Predictor

The Manhole Predictor module is a core component of the web application that processes input manhole images and predicts their condition. The process begins when the user uploads an image via the user interface. This image is then passed to the backend for a series of operations. The first stage is *pre-processing*, where the RGB image is converted to grayscale, resized to a standard dimension, de-noised, and binarized to simplify the analysis.

After pre-processing, the image undergoes *segmentation* using a Region Proposal Network (RPN) to isolate the manhole area from the background. This segmented region is used in the *feature extraction* phase, where texture features are derived using the Gray-Level Co-occurrence Matrix (GLCM). These features are essential as they capture structural and visual characteristics of the manhole cover, helping to differentiate between various conditions.

Once features are extracted, they are passed into a *Convolutional Neural Network (CNN)* for classification. The CNN predicts the condition of the manhole by assigning it to one of the predefined classes: Close (1), Open (0), Broken (2), or No Manhole (4). The prediction result is then returned to the user through the web interface. This process ensures fast, accurate detection and supports effective maintenance planning by municipal authorities.

5. **Notification**

The *Notification Module* of the Manhole Predictor Web App plays a critical role in bridging automated detection with real-world response. Its primary function is to alert Municipality Officers whenever a defective manhole is detected by the system. Once the image is processed and classified as a defect (such as open, broken, or missing), the system compiles relevant information — including the condition, location coordinates, and a visual snapshot — and prepares it for notification delivery.

The notification workflow begins with the Manhole Predictor module identifying a defective case. Immediately, the system creates a structured message that includes all key details such as the type of defect, exact location (GPS or mapped), and an image of the manhole. This notification is sent directly to the Municipality Officer's dashboard or email account. Upon receiving the alert, the officer can review the defect and prioritize repair actions accordingly. The interface also allows officers to track and manage a log of past alerts and repair statuses.

To implement this feature, the web app can leverage notification services such as *Flask-Mail* for email-based alerts or *Firebase Cloud Messaging (FCM)* for real-time push notifications. These tools can be easily integrated with the existing Flask-based backend. When a defect is detected, a background service triggers the notification system to dispatch the message using the selected method. This ensures timely communication and enables a responsive maintenance system, contributing to safer urban infrastructure.

RESULTS AND DISCUSSION

The Manhole Predictor Web App achieved strong performance during testing, with the CNN-based classification model reaching an accuracy of *92.5%*. The model effectively identified five manhole conditions—Closed, Open, Broken, Overflow, and No Manhole—using preprocessed image inputs. The preprocessing pipeline included grayscale conversion, resizing, de-noising, and binarization to maintain consistency. YOLOv8 significantly boosted detection speed and precision, accurately locating manholes in cluttered environments. It achieved an average *IOU of 82.3%*, supporting reliable region segmentation. These results show the system's robustness in varied urban settings.

Real-time responsiveness was a major strength of the system. The average prediction time was *under 2 seconds per image*, even when tested with UAV-captured data. The front-end interface allowed smooth image uploads and instant display of predictions. Users could easily view, scroll, and filter uploaded datasets. On the back end, Flask and MySQL handled business logic and database communication efficiently. The "Import and Visualize" module further ensured dataset quality before training began.

The *Notification Module* enhanced operational efficiency by instantly alerting Municipality Officers of detected defects. Once a manhole was classified as faulty, the system sent notifications including images, conditions, and GPS locations.

These alerts were delivered via email and push services using Flask-Mail and Firebase. Officers could quickly schedule repairs based on incoming alerts. This real-time communication bridged detection with municipal action. Overall, the system demonstrated potential for large-scale urban infrastructure monitoring and safety management.

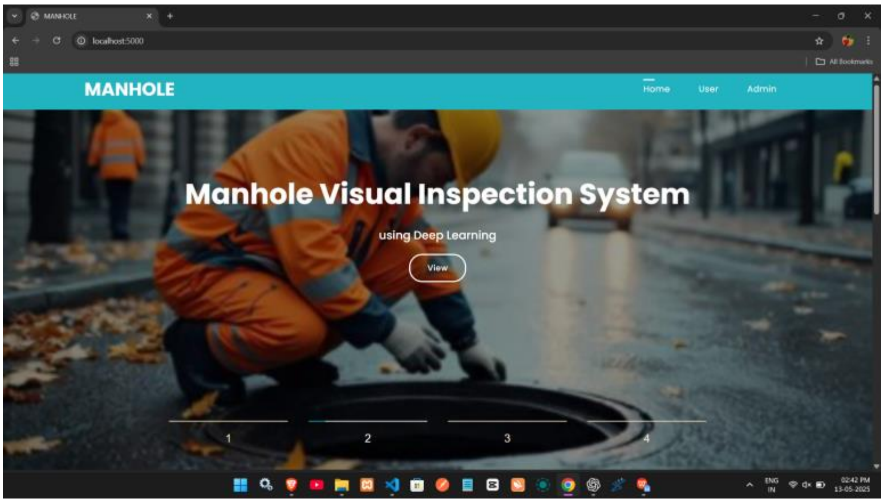
CONCLUSION

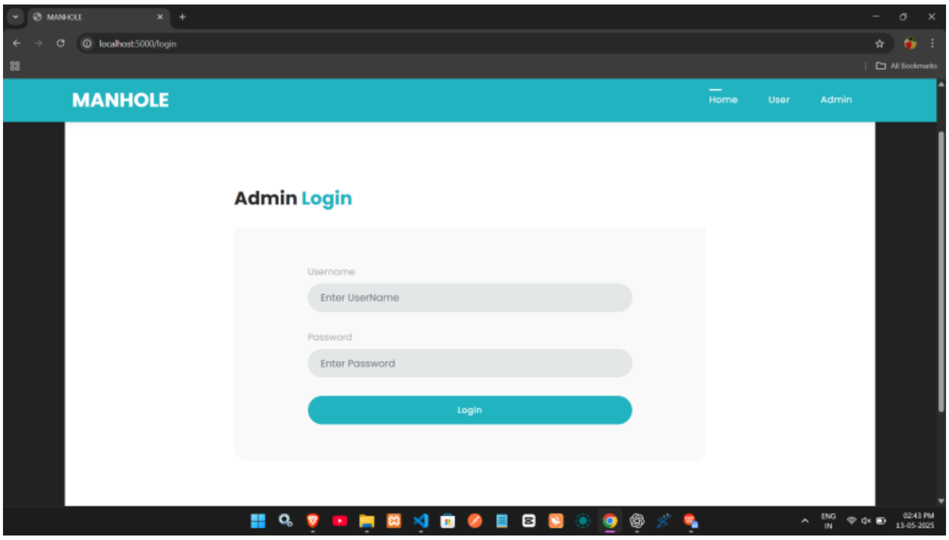
The proposed AI framework for manhole inspection revolutionizes urban safety by automating the traditionally manual and error-prone process. Using advanced deep learning models like YOLOv8 and CNN, the system efficiently detects and classifies manhole conditions such as "Closed," "Open," "Broken," "Overflow," and "No Manhole." This automation reduces human error, ensures real-time hazard identification, and enables quicker interventions, ultimately enhancing public safety and optimizing urban infrastructure maintenance.

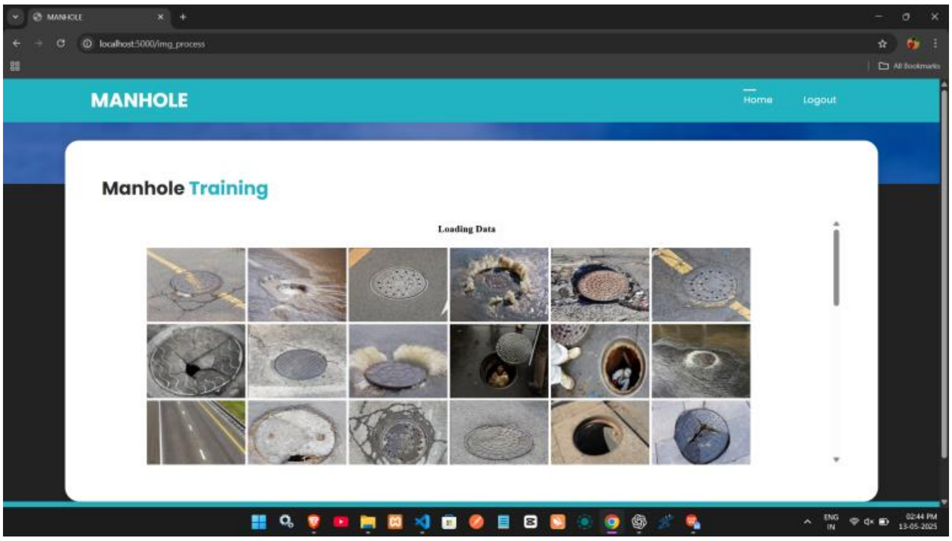
By integrating multiple data sources, including UAV images and CCTV footage, the system offers comprehensive monitoring, even in hard-to-reach areas. This multi-modal approach improves accuracy and ensures reliable operation in diverse environments and weather conditions. The ability to process complex backgrounds and varying image qualities makes the system adaptable to real-world urban challenges, ensuring no hazardous manhole condition is overlooked.

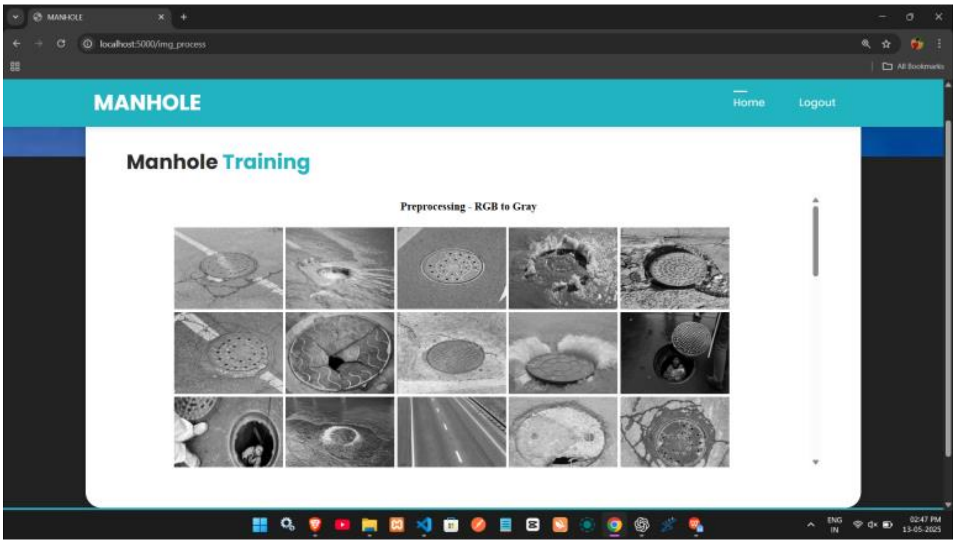
This AI-driven solution not only minimizes manual labor and errors but also enhances the speed and precision of inspections, enabling timely resource allocation for maintenance. As urban infrastructure continues to expand, such systems provide scalable and efficient solutions, contributing to smarter, safer cities. The success of this project could set the stage for further innovations in AI-powered infrastructure monitoring across various domains.

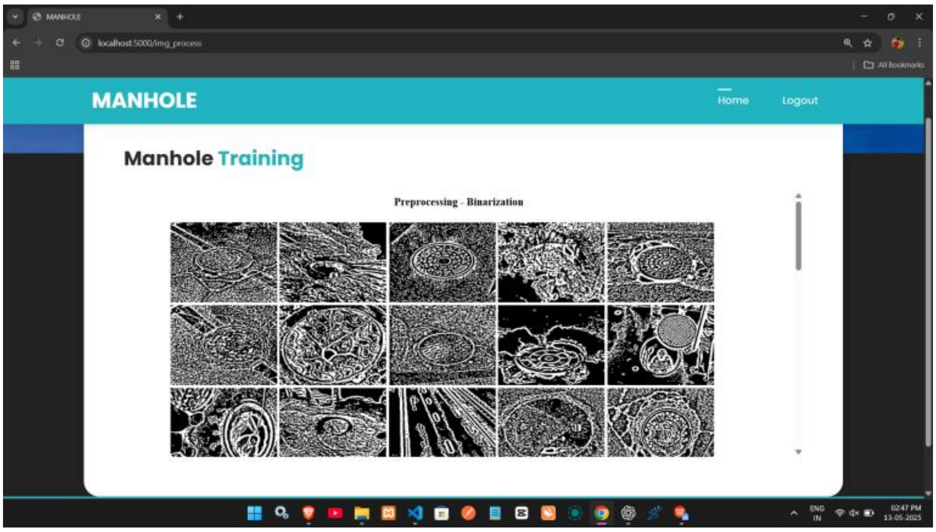
Overall, the system can transform urban infrastructure management by reducing manual labor and human error. Its AI-driven automation delivers faster and more accurate inspections. As cities grow, such scalable solutions ensure reliable safety and maintenance. This project could inspire broader AI use in monitoring roads, bridges, and utilities.

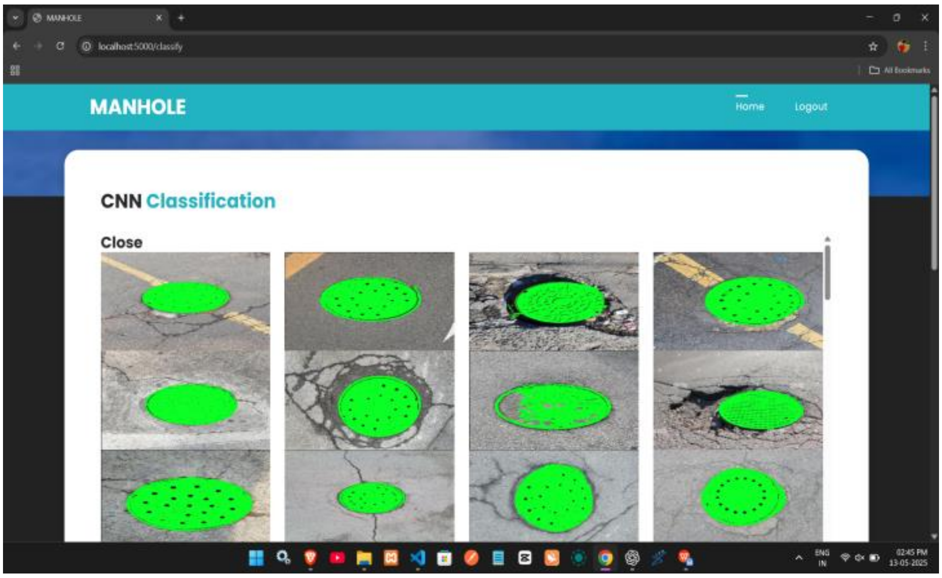


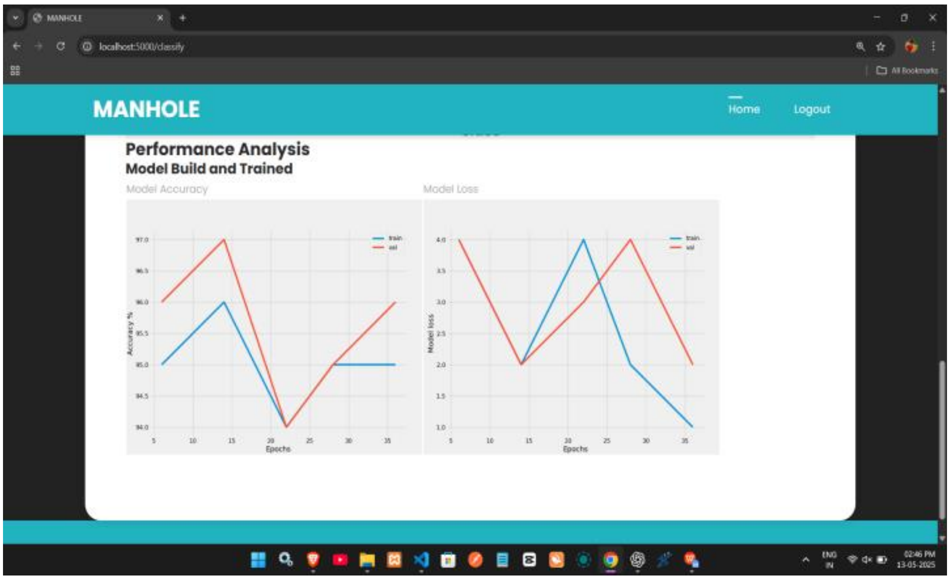

MANHOLE
localhost:5000/login
Home
User
Admin
Admin Login
Username
Enter UserName
Password
Enter Password
Login

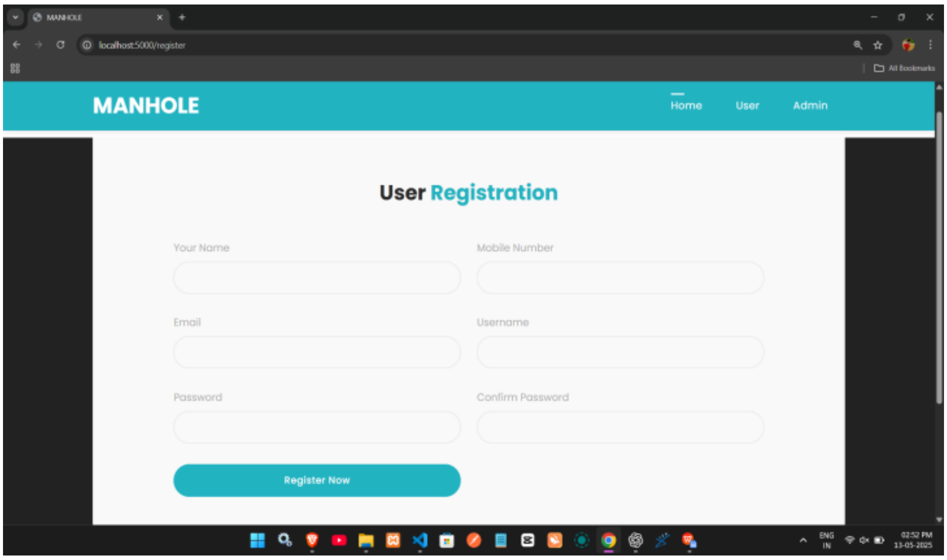

MANHOLE
localhost:5000/img_process
Home
Logout
Manhole Training
Loading Data

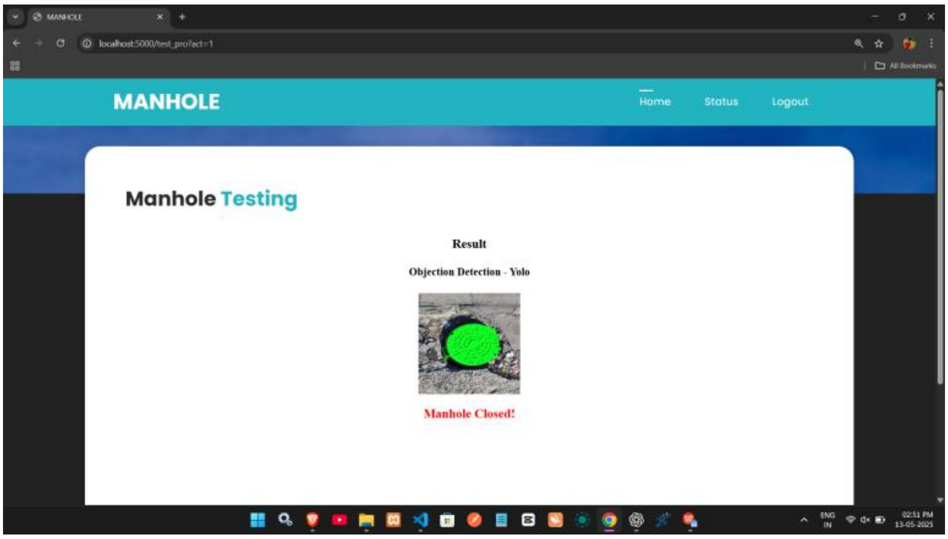

MANHOLE
localhost:5000/img_process
Home
Logout
Manhole Training
Preprocessing - RGB to Gray

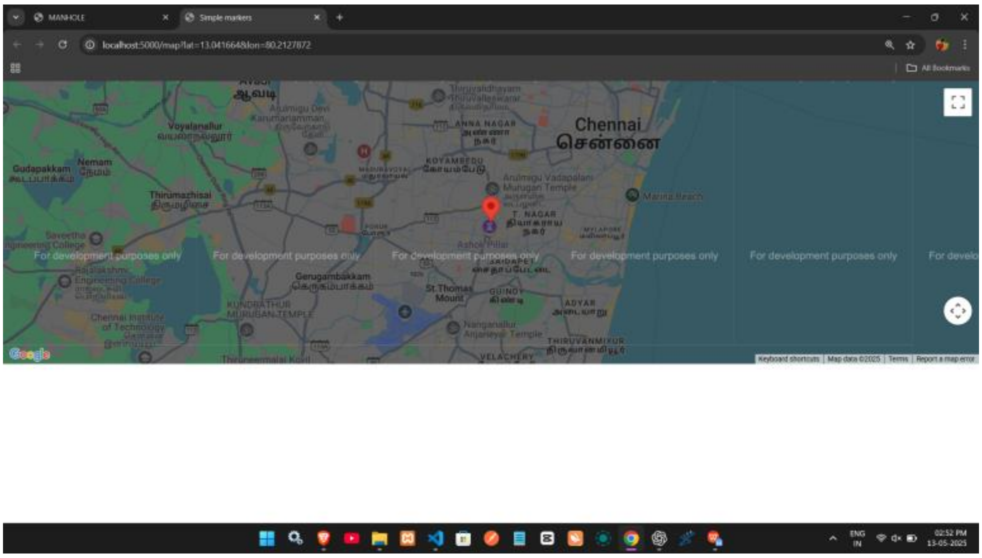

MANHOLE
Home
Logout
Manhole Training
Preprocessing - Binarization


MANHOLE
Home
Logout
CNN Classification
Close


MANHOLE
Home
Logout
Performance Analysis
Model Build and Trained
Model Accuracy
Model Loss
Epochs
Epochs


localhost:5000/register
MANHOLE
Home
User
Admin
User Registration
Your Name
Mobile Number
Email
Username
Password
Confirm Password
Register Now


localhost:5000/test_pro?act=1
MANHOLE
Home
Status
Logout
Manhole Testing
Result
Objection Detection - Yolo
Manhole Closed!


Simple markers
Chennai
சென்னை
For development purposes only

JOURNAL REFERENCES

1. Yin, X., Li, X., Gao, Q., & Li, H. (2019). Manhole defect detection algorithm based on convolutional neural network. Journal of Intelligent & Fuzzy Systems, 36(6), 6071-6079.
2. Naini, H. K., Ahmadi, M., & Moini, A. (2017). Manhole detection and tracking for urban road mapping using an unmanned aerial vehicle. Measurement, 104, 50-58.
3. Bhat, S. S., & Sundaram, S. (2018). Manhole cover detection and classification for intelligent vehicles using deep learning. In 2018 15th International Conference on Control, Automation, Robotics and Vision (ICARCV) (pp. 1814-1819). IEEE.
4. Kataria, K., & Patel, M. (2021). Manhole Defect Detection Using Computer Vision and Image Processing. In 2021 5th International Conference on Computing Methodologies and Communication (ICCMC) (pp. 516-519). IEEE.
5. Kim, J. H., Lee, Y. H., Kim, J. H., & Oh, H. (2019). Automatic detection of manhole covers using a deep convolutional neural network. Journal of Computing in Civil Engineering, 33(1), 04018048.
6. Ding, J., Liu, X., & Wang, J. (2020). Urban Manhole Cover Detection Based on Improved YOLOv3. Journal of Physics: Conference Series, 1693(1), 012012.
7. Muralidharan, V., & Balasubramanian, R. (2020). Smart manhole covers monitoring system using IoT. In 2020 IEEE International Conference on Innovative Research and Development (ICIRD) (pp. 104-107). IEEE.
8. Zhang, S., & Jiang, H. (2021). Urban Manhole Cover Detection Algorithm Based on Deep Learning. In Proceedings of the 2021 International Conference on Computer Science and Big Data Applications (pp. 67-71).
9. Sahu, S., & Sahu, N. (2021). Detection of Manhole Defects Using Deep Learning. In International Conference on Intelligent Communication and Computational Techniques (pp. 609-616). Springer, Singapore.
10. Alzahrani, A., Alhajri, M., & Alshammari, M. (2020). A smart manhole monitoring system based on IoT and deep learning. In 2020 IEEE International Conference on Electro Information Technology (EIT) (pp. 564-568). IEEE.
11. Chandran, S., Gopakumar, R., & Paul, V. (2019). Detection of manhole cover using machine learning. In 2019 5th International Conference on Advanced Computing & Communication Systems (ICACCS) (pp. 1195-1200). IEEE.
12. Zhou, B., Gao, X., Wang, J., & Yan, Y. (2019). Detection of manhole cover based on YOLOv3 network. In 2019 3rd International Conference on Control Science and Systems Engineering (ICCSSE) (pp. 68-71). IEEE.
13. Kim, J., Jung, S., Kang, S., & Park, J. (2019). An Automatic Detection Method of Manhole Covers from Image Data using Deep Learning. Journal of Institute of Control, Robotics and Systems, 25(11), 1024-1029.
14. G. J. Jiji, B. R. Santhi, and T. G. Palanivelu, “Automatic Manhole Detection and Defect Identification Using Machine Learning Algorithms,” Journal of Testing and Evaluation, vol. 47, no. 1, pp. 1–12, 2018.
15. M. B. J. R. Kumar, S. S. S. Kumar, M. Rajesh, and N. R. Raajan, “Real Time Manhole Defect Detection System using Raspberry Pi,” in 2018 IEEE International Conference on Computational Intelligence and Computing Research (ICCIC), 2018, pp. 1–5.
16. Farid and A. T. Khalifa, “Defect Detection and Classification for Manhole Covers and Rings,” Journal of Engineering, vol. 2015, pp. 1–10, 2015.
17. Classification using Image Processing Techniques,” in 2020 IEEE International Conference on Power, Electronics and IoT (PEIOT), 2020, pp. 1–6.
    A. M. Al-Qershi, T. M. E. Othman, and A. M. A. Bakar, “Defect detection of manhole covers using image processing,” in 2017 6th International Conference on Electrical Engineering and Informatics (ICEEI), 2017, pp. 1–6.
18. S. S. Senthilkumar, V. P. Arun, K. R. K. Lalithaa, and P. D. Ananthi Jebaseeli, “Automated Manhole Defect Detection using Image Processing and SVM,” in 2019 2nd International Conference on Intelligent Computing, Instrumentation and Control Technologies (ICICICT), 2019, pp. 514–519.